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Lab session # 4
3D COMPUTER VISION 2023

11/08/23

1 Goal of the lab - Some theory

To recall some definitions from the lecture, a disparity map is a depth map where two cameras have captured the same scene but from slightly different angles. The disparity map represents the difference in horizontal position of corresponding points in the images taken from these two viewpoints as it can be seen in Fig 2. Therefore, the process of computing a disparity map involves finding matching points between the two images and calculating the distance between them.

Graph Cut for Disparity Estimation:

When using a graph cut for disparity estimation, the problem is formulated as a labeling problem where each pixel in the image is assigned a label that corresponds to a particular disparity value as shown in Fig 1. The goal is then to find the most consistent set of labels that minimize a cost function. The optimization is performed using a graph cut algorithm, which treats the problem as a flow network and finds the minimum cut that separates the graph into disjoint sets with the minimum cost. The result is a disparity map that is coherent and respects object boundaries [2] [1].

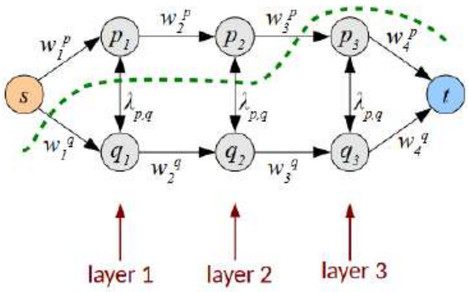

Figure 1: Principle of Linear multi-label graph construction. Adapted from [2].

Seeds Propagation Algorithm:

On the other hand, the seeds propagation algorithm that was studied in the previous lab start with seed points of known disparity and incrementally grow regions by adding neighboring pixels that have similar image characteristics. This approach can be faster and simpler, but it may result in less precise disparity maps. The two images that will be analyzed throughout the lab are the ones in Fig 2.

Figure 2: Face 0 and 1, different viewpoints

2 Graph Cuts algorithm

2.1 Results

The disparity map that has been found is in Fig 3, then the blurred disparity map in Fig 4 and finally the 3D mesh renderings (after the depth map has been computed) is in Fig 5 and the gray rendering is in Fig 6.

Figure 3: Disparity map obtained thanks to the Graph Cut algorithm

Figure 4: Blurred disparity map obtained thanks to the Graph Cut algorithm

Figure 5: 3D mesh renderings after the depth map has been computed

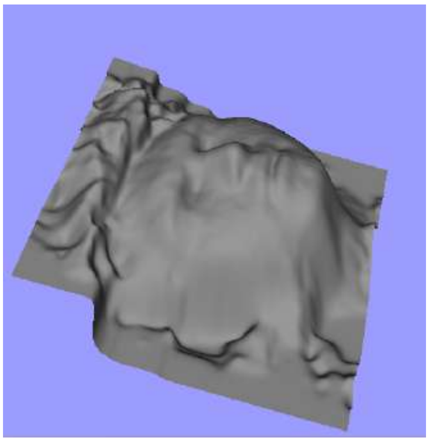

Figure 6: 3D mesh renderings gray rendering

2.2 Interpretation

The algorithm provides satifsying results as there is indeed a good 3D reconstruction at the end, indeed it fits well what we can expect from a real-world scenario. More precisely, the disparity map is detailed and accurate. The blurring has preserved the edges while reducing the noise. We can try to modify some parameters of the algorithm to visualize what are the effects of it on the 3D reconstruction.

Let's modify λ:

λ is the weight of regularization, the smoothing term. By default, $\lambda = 0.1$. If $\lambda = 0.01$ we obtain Fig 7, 8 & 9. If $\lambda = 1$, we obtain Fig 10, 11 & 12.

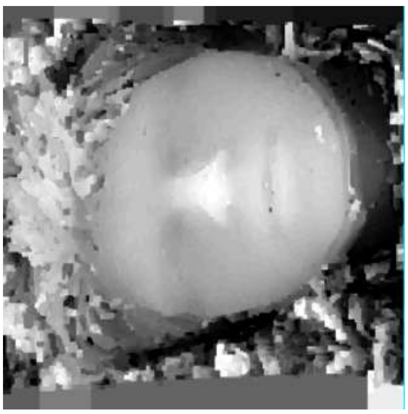

Figure 7: Disparity Map $\lambda = 0.01$

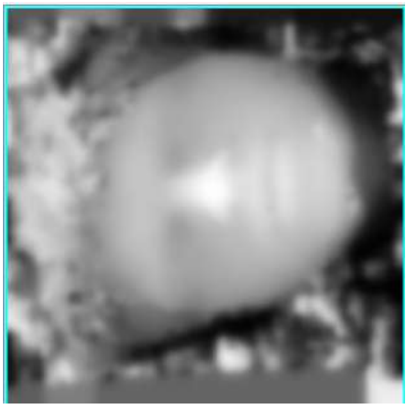

Figure 8: Blurred Disparity Map $\lambda = 0.01$

Figure 9: 3D Mesh Renderings $\lambda = 0.01$

Figure 10: Disparity Map $\lambda = 1$

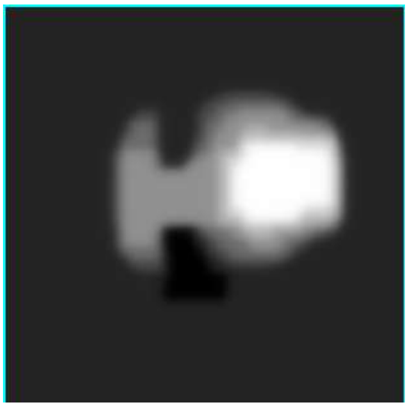

Figure 11: Blurred Disparity Map $\lambda = 1$

Figure 12: 3D Mesh Renderings $\lambda = 1$

What we can observe when we modify λ is that when λ is low the 3D reconstruction is less precise as some peaks appear on the surroundings of it. Indeed, the disparity maps look noisier. These artifacts might then reveal that there is overfitting of the data. On the other hand, when λ is high, the resulting 3D reconstruction is really not efficient as we obtain a flat result. Too high value seems to lead to oversmoothing. It then causes a loss of important details and the performance with object boundaries is less interesting.

Let's modify NCC (window size used for the Normalized Cross-Correlation calculation):

By default, NCC neighborhood size is of 3 pixel radius, i.e 7x7 pixel patch. Let's consider size of 1 pixel radius (3x3 pixel patch) and size of 6 pixel radius (13x13 pixel patch).

Figure 13: Disparity Map NCC 1 pixel radius

Figure 14: Blurred Disparity Map NCC 1 pixel radius

Figure 15: 3D Mesh Renderings NCC 1 pixel radius

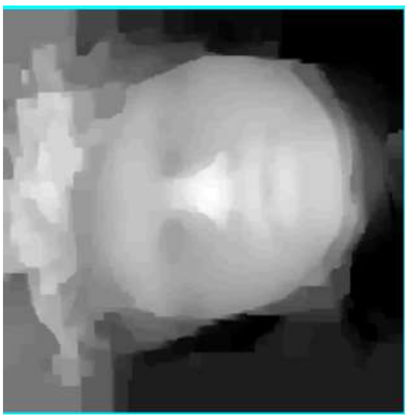

Figure 16: Disparity Map NCC 6 pixel radius

Figure 17: Blurred Disparity Map NCC 6 pixel radius

Figure 18: 3D Mesh Renderings NCC 6 pixel radius

The differences observed do not appear really clearly on the images however we can still conclude that when the NCC window is small, more details are captured and the matching is more precise. On the other hand, when the NCC window is large there are less noise and seems to perform well in low-texture areas even though finer details are lost dut to the averaging over large areas.

Now that we looked at the results obtained thanks to the Graph Cut algorithm, let's compare with the algorithm from last week that was about seeds propagation.

3 Seeds method

3.1 Results

Here are the results obtained with the Seeds method. The disparity map is observed in Fig 19 and the seeds map is observed in Fig 20. Then, the dense map after the seeds propagation is in Fig 21 and the 3D mesh rendering is in Fig 22.

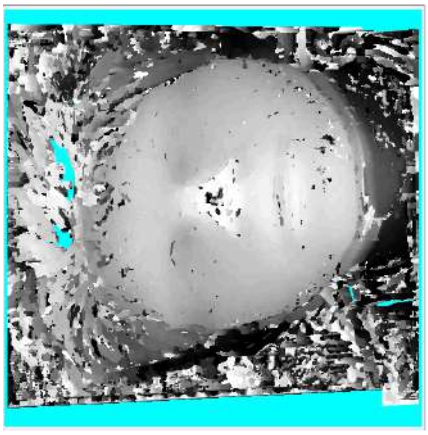

Figure 19: Dense map obtained with the seeds method

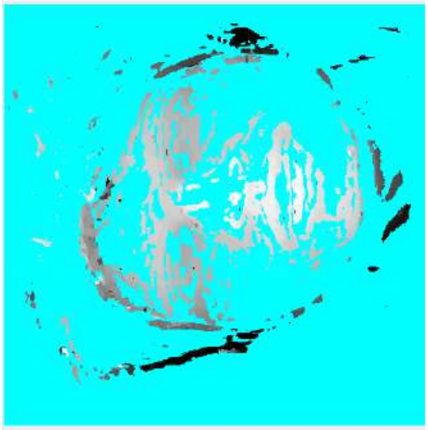

Figure 20: Seeds map obtained with the seeds method

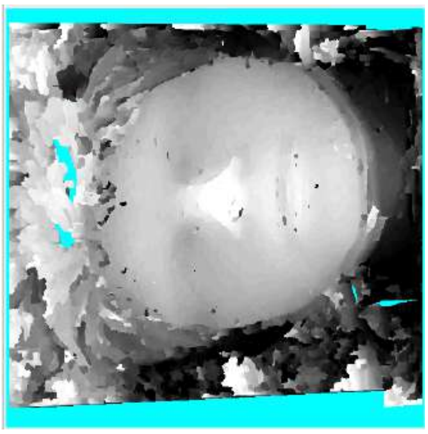

Figure 21: Dense map after seeds propagation

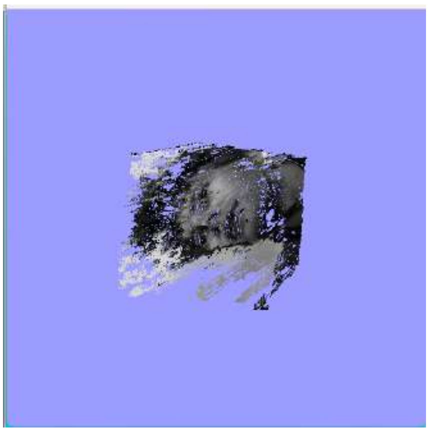

Figure 22: 3D mesh renderings

3.2 Interpretation

We observe that the 3D results is very different from the result with the graph cut method. There are many artefacts in the disparity map and the 3D mesh is really far from reality. It might comes from the fact that there are no regularization term in this method and no global optimization. Indeed the regulariation term helps to impose smoothness constraints on the disparity map.

4 Methods comparison

- **Precision:** Graph cut algorithms seems to provide more precise disparity maps than seeds propagation method. Indeed, graph cuts method looks at the global image information and optimize a global cost function, making it more robust.
- **Smoothness:** Graph cuts appears to produce smoother disparity maps with well-preserved edges due to the smoothness term in the cost function. In contrast, seeds propagation algorithms may provide less smooth results and can be sensitive to the placement of seed points.
- **Computation Time:** Graph cut algorithms are more computationally intensive than seeds propagation method due to the complexity of the optimization process. Seeds method can be faster. We observe indeed that the computation time for seeds method is 10 s and 18 s with graph cuts.

5 Test with other images

We can try to compare our different methods with the images from the previous lab on seeds propagation, with the image of the toys. The result of the disparity map thanks to graph cuts method is displayed in Fig 23, Fig 24 & 25. Similar results are obtained thanks to the seeds propagation method as the disparity map is obtained in Fig 26, the disparity map after seeds propagation in Fig 27 and the 3D Mesh rendering in Fig 28.

Figure 23: Disparity Map Toys Image Graph Cut method

Figure 24: Blurred Disparity Map Toys Image Graph Cut method

Figure 25: 3D Mesh Renderings Toys Image Graph Cut method

Figure 26: Disparity Map Toys Image Seeds method

Figure 27: Propagated Disparity Map Toys Image Seeds method

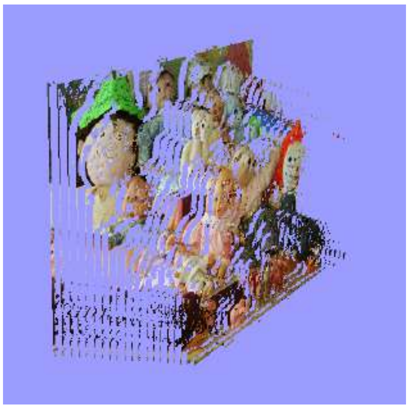

Figure 28: 3D Mesh Renderings Toys Image Seeds method

What we observe with this new example is that the disparity map is similar in both methods even though the disparity map is less noisy with the graph cuts method. Furthermore, the 3D mesh rendering for graph cuts method respects more the boundary of objects.

6 Conclusion & Outlooks

In conclusion, whereas graph cut approache provides more precision and smoothness, it is also more computationally demanding. The choice between a graph cut and a region-growing approach would be determined by the application's specific needs, such as the necessity for real-time processing against the need for high accuracy.

References

[1] Y. Boykov and O Veksler. Graph cuts in vision and graphics: Theories and applications. In *Handbook of Mathematical Models in Computer Vision, edited by Nikos Paragios, Yunmei Chen and Olivier Faugeras. Springer.*, 2006.

[2] Pascal Monasse Renaud Marlet. Graph cuts and application to disparity map estimation. In *MVA/IMA, 3D Computer Vision*, 2023.